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# 2 Programming Problems

# 2.1 Data Description

This dataset shows the measurements of the geometrical properties of kernels belonging to three different varieties of wheat. Table 3 shows some statistics of the given dataset.

Table	≥ 3:	Data	description
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	0	1	2	3	4	5	6	7
count	210.000000	210.000000	210.000000	210.000000	210.000000	210.000000	210.000000	210.000000
mean	14.847524	14.559286	0.870999	5.628533	3.258605	3.700201	5.408071	2.000000
$\operatorname{std}$	2.909699	1.305959	0.023629	0.443063	0.377714	1.503557	0.491480	0.818448
min	10.590000	12.410000	0.808100	4.899000	2.630000	0.765100	4.519000	1.000000
25%	12.270000	13.450000	0.856900	5.262250	2.944000	2.561500	5.045000	1.000000
50%	14.355000	14.320000	0.873450	5.523500	3.237000	3.599000	5.223000	2.000000
75%	17.305000	15.715000	0.887775	5.979750	3.561750	4.768750	5.877000	3.000000
max	21.180000	17.250000	0.918300	6.675000	4.033000	8.456000	6.550000	3.000000

The first 7 columns are attributes data, and the last column gives the label information.

### 2.2 PCA

Following the steps given in Section 1.3, we project the original data into a twodimensional subspace. Figure 3 shows the PCA results.

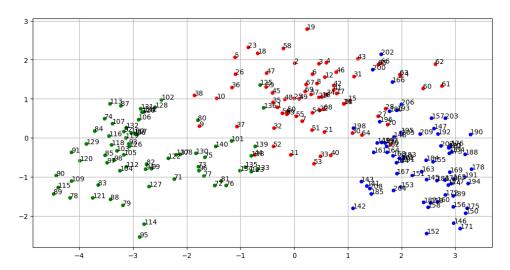


Figure 3: PCA results

The data are colored by true labels. Then, we will implement the K-means to cluster these data.

#### 2.3 K-means

For the K-means method, we follow the steps below:



- a) Randomly choose K distinct centroids, and here K=3
- b) Compute the distance between each data point and the centroid
- c) Assign each data point to the nearest centroid, to form a cluster
- d) Calculate the mean of each cluster as the new centroid
- e) Repeat Step b)-d) until converge. Here I set the convergence tolerance as 0.0001 Following the above steps, we can derive our K-means clustering results. See Figure 4

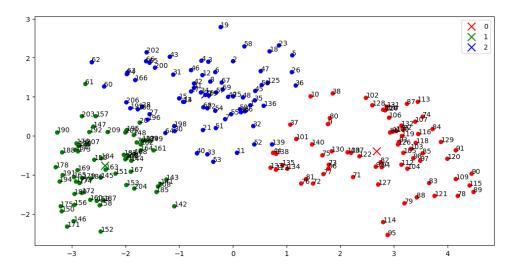


Figure 4: K-means results

## 2.4 Performance Evaluation

### 2.4.1 Silhouette Coefficient

We define

- a: The mean distance between a point and all other points in the same cluster
- b: The mean distance between a point and all other points in the **next nearest** cluster

And the Silhouette coefficient for a single sample is defined as

$$s = \frac{b - a}{\max(a, b)}$$

Larger s indicates better clustering performance. The Silhouette coefficient of our clustering result is 0.4732



#### 2.4.2 Rand Index

Then, we apply an external evaluation matrix. Similarly, we define

- a: The number of pairs of elements in S that are in the **same** subset in X and in the **same** subset in Y
- b: The number of pairs of elements in S that are in the **different** subset in X and in the **different** subset in Y
- c: The number of pairs of elements in S that are in the **same** subset in X and in the **different** subset in Y
- d: The number of pairs of elements in S that are in the **different** subset in X and in the **same** subset in Y

And the Rand Index is defined as

$$RI = \frac{a+b}{a+b+c+d} = \frac{TP+TN}{TP+TN+FP+FN}$$